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STRUCTURE OF FUZZY CONTROL MODULE WITH NEURAL NETWORK

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ABSTRACT

The paper deals with the fuzzy control module's structure, which has the property that is deficit in "conventional" uncertain systems - the skill to learn. This is attained by offering the control module in the form of a neural-like multi-layer network. At the same time, this system is free from the main disadvantage of neural networks - the knowledge distribution. All parameters and weights retain their physical understanding, which makes it likely to examine the information gathered by the system in the process of learning.

KEYWORDS: Fuzzy Set Theory, Neural Networks, Learning, Control, Fuzzification & Defuzzification

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Original Article

1. INTRODUCTION

The most significant advantage of neural networks is the possibility of their adaptation and learning. We do not need facts about the object of management in the form of its mathematical model. Neural networks include huge number of unified simple processing essentials (neurons), which therefore offers great computing power when using parallel processing of data. Based on the involvement and quantified reference signals, the neural network can learn to control the object. Unfortunately, the design of such systems is based more on perception than on prevailing patterns. Until now, the algorithm for scheming the number of neurons and the number of network layers in each layer for detailed claims are unidentified. However, upon the end of training, neural networks become crucial tools for resolving problems of pattern recognition, optimization, approximation, vector classification or quantization. On the contrast, the information gathered by the neural network is dispersed among all its elements, which makes them almost unreachable to the spectator. [1].

This nonexistence of control systems with uncertain logic. Nevertheless, in this case, management knowledge method is already necessary at the control modules' design stage, and they should come from experts, therefore, there is no option of training. However, even in such a condition, comprehensive information (explaining the functional need between the outputs and inputs of the system in mathematical form) is not essential. Unlike conservative control modules, quantitative rather than qualitative information is used. The system decides based on the guidelines written in the form of an IF-THEN inference. The meekest method to scheming such systems is to express management membership and rules functions from the consequences of monitoring the management process carried out by an individual or a current controller, and then evaluating the correct working of such a system. If the plan is ineffective, the membership function and / or management rules can be altered easily. As noted already, the main disadvantage of such systems is the impossibility of learning and adaptation. [2-7].

Grouping of both methods permits, on the one hand, to bring computational power and learning ability of neural networks into systems with uncertain logic, and on the other hand, to improve the intelligent competences of

neural networks characteristic of the “human” way of thinking with uncertain decision-making instructions [1,8].

We explain the module fuzzy control’s structure.

2. THE MODULE STRUCTURE OF FUZZY CONTROL

- Rules database. The information that forms the foundation of the right working of the fuzzy control module is noted in the form of a uncertain rule having the form [1,5]

$$R^k : IF\left(x_1\, is\, A_1^k\ AND \ldots AND\, x_n\, is\, A_n^k\right) THEN \left(y\, is\, B^k\right).$$

If the operation of multiplication is used as a fuzzy suggestion, we get the formula

$$\mu_{A^k \to B^k}(x,y) = \mu_{A^k}(x)\mu_{B^k}(y). \tag{1}$$

The Cartesian product of fuzzy sets can be represented in the form when used,

$$\mu_{A^k}(x) = \mu_{A_1^k \times \ldots \times A_n^k}(x) = \mu_{A_1^k}(x_1)\ldots\mu_{A_n^k}(x_n) \tag{2}$$

- Output unit. We offer a formula defining the membership function of a uncertain set $\overline{B}^k$

$$\mu_{\overline{B}^k}(y) = \sup_{x\in X}\left\{\mu_{A^{'}}(x)^T * \mu_{A^k \to B^k}(x,y)\right\}. \tag{3}$$

The exact form of this function depends on the applied T-norm, the fuzzy implication definition and on the process of defining the Cartesian product of fuzzy sets. T-norm can be signified as a product form

$$\sup_{x\in X}\left\{\mu_{A^{'}}(x)^T * \mu_{A^k \to B^k}(x,y)\right\} = \sup_{x\in X}\left\{\mu_{A^{'}}(x)\mu_{A^k \to B^k}(x,y)\right\}. \tag{4}$$

Because of uniting the above terms, you can achieve the following alteration:

$$\begin{aligned}
\mu_{\overline{B}^k}(y) &= \sup_{x\in X}\left\{\mu_{A^{'}}(x)^T * \mu_{A^k \to B^k}(x,y)\right\} = \\
&= \sup_{x\in X}\left\{\mu_{A^{'}}(x)\mu_{A^k \to B^k}(x,y)\right\} = \\
&= \sup_{x\in X}\left\{\mu_{A^{'}}(x)\mu_{A^k}(x)\mu_{B^k}(y)\right\} = \\
&= \sup_{x_1,\ldots,x_n\in X}\left\{\mu_{A_1^{'}}(x_1)\ldots\mu_{A_n^{'}}(x_n)\mu_{A_1^k}(x_1)\ldots\mu_{A_n^k}(x_n)\mu_{B^k}(y)\right\},
\end{aligned}$$

$$\mu_{\overline{B}^k}(y) = \sup_{x_1,\ldots,x_n\in X}\left\{\mu_{B^k}(y)\prod_{i=1}^{n}\mu_{A_i^{'}}(x_i)\mu_{A_i^k}(x_i)\right\}. \tag{5}$$

- Fuzzification block. Let's apply action like singleton

$$A^{'}(x) = \begin{cases} 1,\ if\ \ x = \overline{x}, \\ 0,\ if\ \ x \neq \overline{x}. \end{cases} \tag{6}$$

In formula (5), note that the supremum is attained only in the case when $x=\overline{x}$, i. e. for $\mu_{A'}(\overline{x})=1$. The appearance (5) takes the form

$$\mu_{\overline{B}^k}(y)=\mu_{B^k}(y)\prod_{i=1}^{n}\mu_{A_i^k}(\overline{x}_i). \tag{7}$$

- Defuzzification block. We apply the centralized defuzzification method, according to which

$$\overline{y}=\frac{\sum_{k=1}^{N}\overline{y}^k\mu_{\overline{B}^k}\left(\overline{y}^k\right)}{\sum_{k=1}^{N}\mu_{\overline{B}^k}\left(\overline{y}^k\right)}. \tag{8}$$

In the above method $\overline{y}^k$ - this is the fuzzy set B^k center, i. e. the fact at which $\mu_{B^k}(y)$ reaches maximum value

$$\mu_{B^k}\left(\overline{y}^k\right)=\max_{y}\left\{\mu_{B^k}(y)\right\}.$$

In the formula (8), when substituting the expression (7) we find the equality

$$\overline{y}=\frac{\sum_{k=1}^{N}\overline{y}^k\left(\mu_{B^k}\left(\overline{y}^k\right)\prod_{i=1}^{n}\mu_{B_i^k}(\overline{x}_i)\right)}{\sum_{k=1}^{N}\left(\mu_{B^k}\left(\overline{y}^k\right)\prod_{i=1}^{n}\mu_{A_i^k}(\overline{x}_i)\right)}. \tag{9}$$

If you study that the extreme value that $\mu_{B^k}\left(y^k\right)$ can get at the point $\overline{y}^k$, equals 1, i. e.

$$\mu_{B^k}\left(\overline{y}^k\right)=1, \tag{10}$$

then the formula (9) becomes

$$\overline{y}=\frac{\sum_{k=1}^{N}\overline{y}^k\left(\prod_{i=1}^{n}\mu_{A_i^k}(\overline{x}_i)\right)}{\sum_{k=1}^{N}\left(\prod_{i=1}^{n}\mu_{A_i^k}(\overline{x}_i)\right)}. \tag{11}$$

- The last stage in the process of scheming a fuzzy control module is the description of the form of depiction of uncertain sets. $A_i^k, i=1,\ldots,n; k=1,\ldots,N.$

For instance, this may be a Gaussian function.

$$\mu_{A_i^k}(x_1) = \exp\left[-\left(\frac{x_i - \overline{x}_i^k}{\sigma_i^k}\right)^2\right], \tag{12}$$

where parameters $\overline{x}_i^k$ and σ_i^k have a bodily clarification: $\overline{x}_i^k$ - it is the middle as well σ_i^k - breadth of a Gaussian curve.

These limits can be altered during learning, which permits changing the structure and position of fuzzy sets.

Now mix all the presented elements. The defuse method (8) is used, the output according to look (5), the fuzzy block with the Gaussian membership function (12), the singleton type operation (6), and then the fuzzy control module accepts the last form.

$$\overline{y} = \frac{\sum_{k=1}^{N} \overline{y}^k \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{\overline{x}_i - \overline{x}_i^k}{\sigma_i^k}\right)^2\right]\right)}{\sum_{k=1}^{N} \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{\overline{x}_i - \overline{x}_i^k}{\sigma_i^k}\right)^2\right]\right)}. \tag{13}$$

The necessities for the excellence of goods formed day after day by automatic means of creation at large creativities are growing. In the automation of production, robots are of particular interest.

A literature examination has revealed that the unusual advantages of the results on controlling and modeling the movement of a robot on a regular basis, related to the movement system accuracy, the control system and the movement model, are as follows [9,10]:

- The control system is deterministic.
- Motion identification system.
- Motion is explained by a nonlinear differential equation

The drawbacks of the model are as follows:

- in the model does not study the nonlinear nature of the forces created by the drive of the robot on the linking nodes;
- the gravity force is considered when the robot moves with the part only when modeling the last link movement - an exciting element; when modeling the remaining intermediate links' motion, this power factor is not taken into consideration;

These features, which were not measured when building a model of motion, also affect the optimal robot control's mathematical model. Therefore, there is a common difference of the routes of motion — dynamic errors — and there will be a decrease in the positional accuracy.

Based on the evaluation of the modern problems of the considered scientific field, a new method to solving the trending issues have been proposed.

For instance, if a convinced linguistic time signifies the robot speed, then a fixed number of fuzzy sets of the kind “medium”, “slow”, “fast” is set for it, and it is on their base that the matching rules are designed.

3. THE DUTY OF THE ROBOT MOVEMENT AND THE WAY OF FORMING FUZZY RULES BASED ON NUMERICAL DATA USING THE ALGORITHM OF ACCUMULATION OF KNOWLEDGE

Let us apply an altered fuzzy control module with the option to solve that problem. In the first point, the module structure was selected. For the primary input signal - the location of the robot on the x axis - it is anticipated to use five membership purposes, and for the second input signal - the angle ϕ, under which the robot is situated on the y-axis - seven membership purposes. Because of producing the properties of fuzzy guidelines based on a pairwise assessment of all the relationship purposes of the first and second variables, 5x 7 = 35 rules are attained. The membership function centers of the output variable (the angle of rotation of the robot θ) are positioned in point 0, which is equal to the nonappearance of conclusions (conclusions) in the guidelines. The original membership purposes thus fashioned were used in the fuzzy control unit by stipulating the corresponding initial values of weights and parameters.

The accuracy of the network functioning was patterned by demonstrating for three diverse initial situations of the robot.

Thus, the existing module structure of a fuzzy control has a property that is inattentive in “ordinary” fuzzy systems — the skill to learn. This is attained by offering the control module in the procedure of a neural-like multilayer network. At the same time, this network is permitted from the key drawback of neural networks - the knowledge distribution. All parameters and weights recollect their physical explanation, which makes it imaginable to examine the knowledge collected by the organization in the process of learning.

Now, we show that the fuzzy control module can be signified as a normal neural network.

We transform expression (7), considering formulas (10) and (12), explaining the membership function of a fuzzy set B^k, to form

$$\mu_{\overline{B}^k}\left(\overline{y}^k\right)=\prod_{i=1}^{n}\exp\left[-\left(\frac{\overline{x}_i-\overline{x}_i^k}{\sigma_i^k}\right)^2\right]. \tag{14}$$

When substituting basic dependencies

$$\prod_{i=1}^{n}\exp(x_i)=\exp\left(\sum_{i=1}^{n}x_i\right)$$

We get from expression (14)

$$\mu_{\overline{B}^k}\left(\overline{y}^k\right)=\exp\left[\sum_{i=1}^{n}-\left(\frac{\overline{x}_i-\overline{x}_i^k}{\sigma_i^k}\right)^2\right]. \tag{15}$$

For easiness, we undertake that the breadth of the Gauss function remains endless for any i, i. e. $\forall i:\sigma_i^k=\sigma k.$ Therefore, you can write

$$\mu_{\overline{B}^k}\left(\overline{y}^k\right)=\exp\left[-\frac{\sum_{i=1}^{n}\left(\overline{x}_i-\overline{x}_i^k\right)^2}{\left(\sigma^k\right)^2}\right]. \tag{16}$$

Continue the conversion:

$$\mu_{\overline{B}^k}\left(\overline{y}^k\right)=\exp\left[-\frac{\sum_{i=1}^{n}\left\{(\overline{x}_i)^2-2\overline{x}_i\overline{x}_i^k+\left(\overline{x}_i^k\right)^2\right\}}{\left(\sigma^k\right)^2}\right]=$$

$$=\exp\left[-\frac{\sum_{i=1}^{n}(\overline{x}_i)^2-\sum_{i=1}^{n}2\overline{x}_i\overline{x}_i^k+\sum_{i=1}^{n}\left(\overline{x}_i^k\right)^2}{\left(\sigma^k\right)^2}\right]. \tag{17}$$

To shorten the above equation, you can regularize the vectors $\overline{x}=\left[\overline{x}_1,\ldots,\overline{x}_n\right]^T$ and $\overline{x}^k=\left[\overline{x}_1^k,\ldots,\overline{x}_n^k\right]^T$, those undertake that their length is 1.

$$\left|\overline{x}\right|=\sqrt{\sum_{i=1}^{n}(\overline{x}_i)^2}=1 \text{ и } \left|\overline{x}^k\right|=\sqrt{\sum_{i=1}^{n}\left(\overline{x}_i^k\right)^2}=1. \tag{18}$$

The dependence (27) can be altered to the form in this case

$$\mu_{\overline{B}^k}\left(\overline{y}^k\right)=\exp\left[-\frac{2-2\sum_{i=1}^{n}\overline{x}_i\overline{x}_i^k}{\left(\sigma^k\right)^2}\right]. \tag{19}$$

Eventually

$$\mu_{\overline{B}^k}\left(\overline{y}^k\right)=\exp\left[h^k\left(\sum_{i=1}^{n}\overline{x}_i\overline{x}_i^k-1\right)\right],\ \text{где}\ h^k=\frac{2}{\left(\sigma^k\right)^2}. \tag{20}$$

When replacing the specified expression into the formula explaining the defuzzification operation (8), we obtain

$$\mu_{\overline{B}^k}\left(\overline{y}^k\right)\overline{y}=\frac{\sum_{i=1}^{n}\overline{y}^k\exp\left[h^k\left(\sum_{i=1}^{n}\overline{x}_i\overline{x}_i^k-1\right)\right]}{\sum_{i=1}^{n}\exp\left[h^k\left(\sum_{i=1}^{n}\overline{x}_i\overline{x}_i^k-1\right)\right]}. \tag{21}$$

The modification of equation (13) is the resulting solution.

4. FUZZY CONTROL WITH THE ABILITY TO CORRECT THE RULES

When designing edifices, it was presumed that the controlling method of an article is identified. Based on this data, fuzzy functions and rules of fitting were created. The training of the structures formed permitted the "achievement" of the membership purpose, but the authentication of the quantified fuzzy rules was not probable. Thus, the output control signal could include an error caused by not quite correct rules.

One of the major difficulties rising during calculating units of fuzzy control is to properly build the membership function and to regulate right fuzzy rules based on them. The algorithm is divided into two points: a) the phase of previously well-known training with the teacher (also called supervised training), b) the learning stage based on self-organization, which permits you to explain the primary membership purposes with the succeeding development of strange rules on their foundation

Learning Stage Based on Self-Organization

- Fixing membership functions. Till the current moment when making the control module structure, we continued from the fact that both the membership purposes of the associated fuzzy rules and the fuzzy sets should be identified (at least in the first calculation). Only based on this information, there could be a creation of the structure with the initial membership functions and with a rule base understood in the method of elements connections of a neural network. The determination of training was involved only in the ideal edition of the membership functions so that the mistake at the output of the fuzzy control module was negligible.

To start learning, it is essential to select a way to isolate each space of output and input variables. In other words, for each verbal variable, it is essential to stipulate its verbal values, which become the fuzzy sets names, and regulate the structure and placement of the matching membership purposes. Of course, it is likely to use one of the formerly measured approaches to place the membership functions seeing the intuition and knowledge of specialists or to allocate them simply consistently.

In the existence of training data in the form of pairs ($\overline{x}$, *d)* in the case of setting the number of fuzzy sets, you can use one of the approaches of training based on self-organization, like statistical grouping (statistical clustering). We are talking about such a preparation of the membership function centers so that they cover only those parts of the output and input spaces in which the data are situated. To attain this aim, one can apply well-known viable teaming approaches. [1].

- Structure formation. Before happening with the rule's construction, a primary structure of the network essential for this must be formed.
- Fixing fuzzy rules. The mission of this phase is to concept right fuzzy rules based on the training information using the parting of output and input spaces achieved at the first phase, as well as primary selection of the membership functions form.
- Rules elimination. The exact state of the rule is coordinated by only one inference. In the situation when the masses of all pledges are insignificant, they are all omitted, and it is measured that this law does not have an important effect on the output variable.
- Combining the rules. After building the rules conclusions, you can go to the stage of decreasing their number by uniting. Definite rules (their conditions, more precisely) are showed by the second layer elements. The resulting criteria can be used to unite the elements of a layer:
  - the guidelines have the same inference
  - some situations of the guidelines are the same;
  - - Some conditions of rules form a full names set of the meaning of a linguistic variable.

This phase may be bounced; if the rules base is recognized, then the expert's duty will be to form the primary membership methods and to begin connections due to these guidelines.

After forming the building fuzzy rules and the network structure, you can go to the next phase - to select the membership functions parameters. All network links and elements formed in the former step are immobile and remain unaffected. The network (including the third- and fourth-layers elements) will spread the indicator in the onward way.

- Refinement of membership functions.

Study the usage of fuzzy systems with traditional (one-dimensional) membership functions to resolve the issue of robot movement. Figure 1 shows a graphical depiction of the so-called key space for a non-explicit system with simplistic membership purposes.

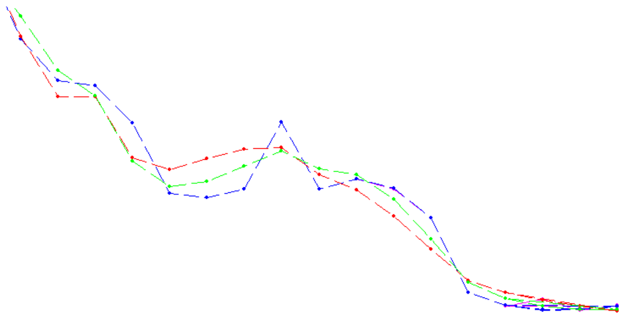

Figure 1: Trajectories of Robot Movement for Three Initial Positions

5. CONCLUSIONS

As a consequence of the robotic systems analysis, it was exposed that the current mathematical replicas and controls do not offer a high extent of speed of the robots movement.

An equation for the robots functioning is attained when executing a complex three-dimensional process and a mathematical model of fuzzy control is established on its base.

The advantages of the measured method contain:

- systematizing the alteration of the involvement function when the situation changes, which is offered by the training chances of neural networks;
- automating the fuzzy rules separation and the membership functions choice.

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